



# Retrieving chlorophyll concentration from GOES-R advanced baseline imager using deep learning

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# Motivation



- Ocean color

Higher spectral, spatial, temporal resolutions

- Geostationary ocean color

GOCI, launched 2010; GOCI-II, launched 2020  
GEOCAPE, launch date TBD

South Korea  
USA

- Geostationary weather satellites

- Advanced Himawari Imager (AHI) / Himawari-8

470 nm 510 nm 640 nm

Japan

[Murakami, 2016]

- Advanced Baseline Imager (ABI) / GOES-R

470 nm 640 nm

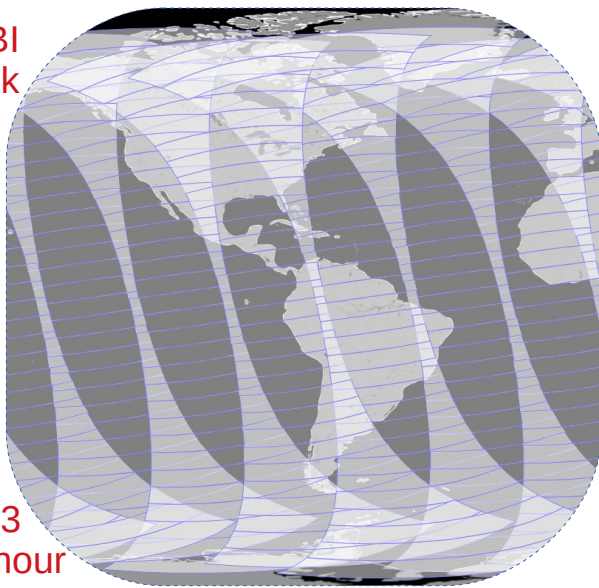
USA



# Matchup **ABI** with **VIIRS**

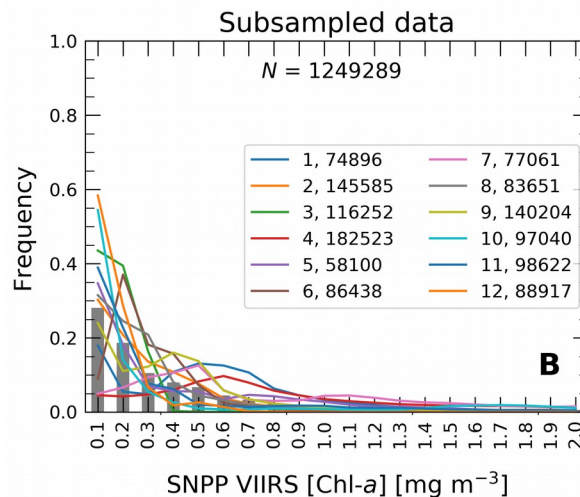
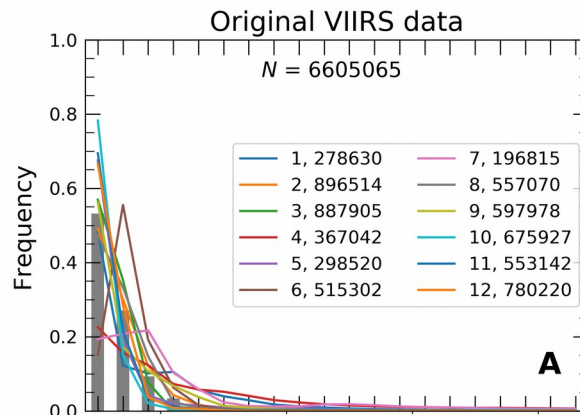
- Selected Jan 21 – Dec 21, 12 days in 2018
- $\pm 2$  hours, cloud masked
- Subsampled to have more balanced [Chl-a] distribution

ABI  
Full Disk



Mode 3  
4 scans/hour

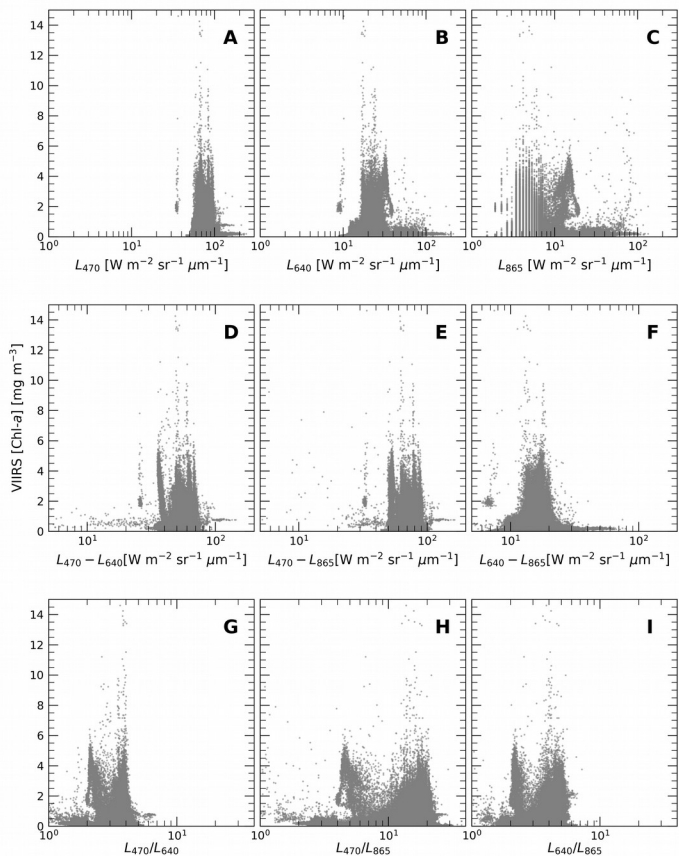
VIIRS  
~1:30 pm  
equator  
crossing



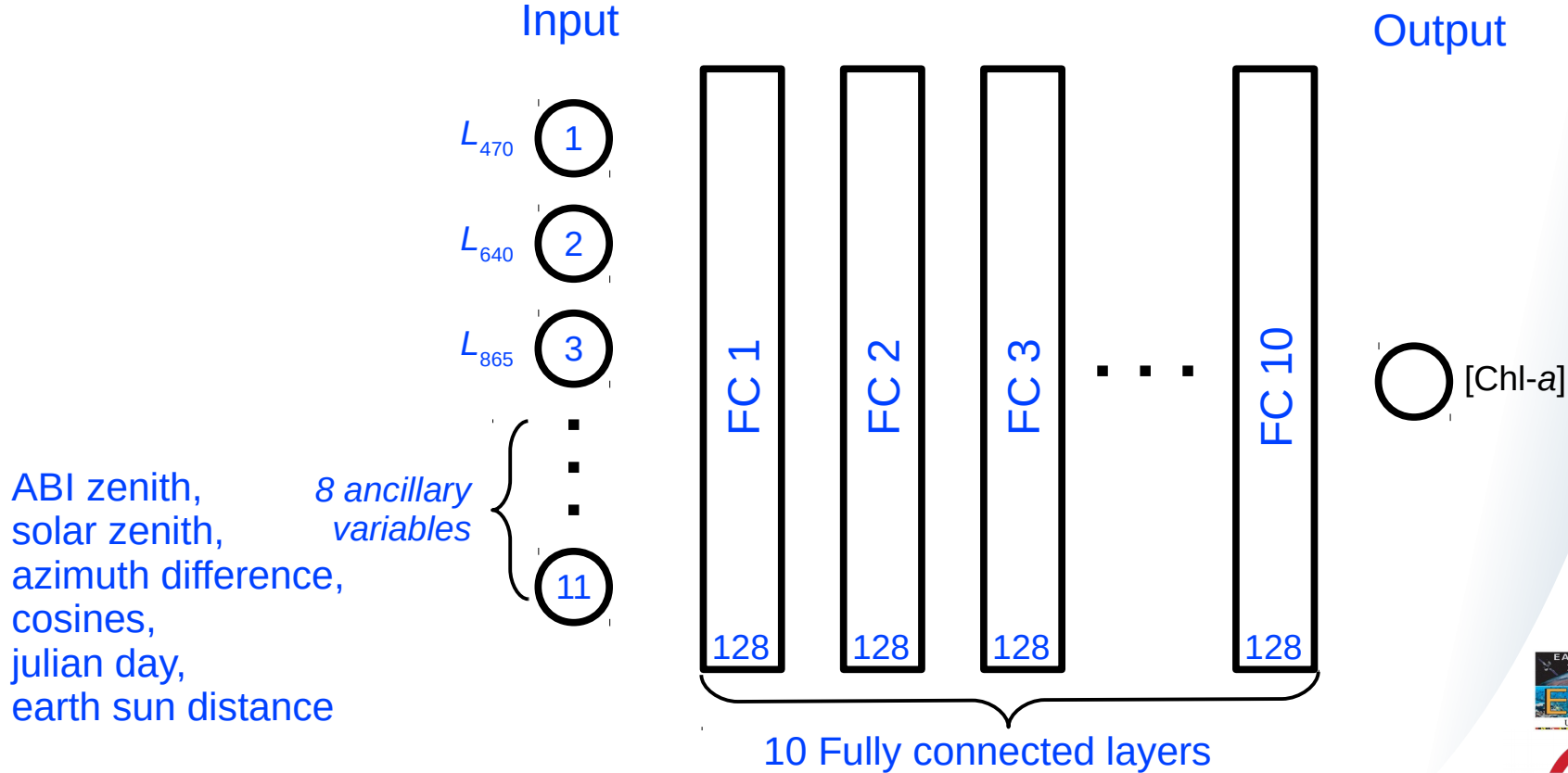
# Raw ABI Data vs. VIIRS-derived [Chl-a]



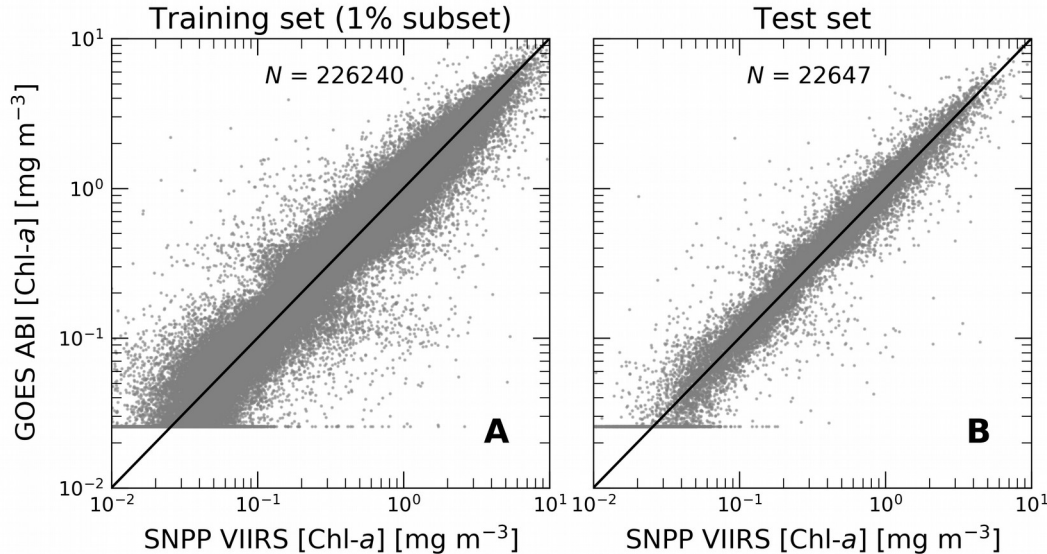
- No atmospheric correction applied on ABI radiance data
- No visible correlation between ABI bands and VIIRS [Chl-a] values



# Model Architecture



# ABI- vs. VIIRS-derived [Chl-a]



- Good agreement
- Artifact at very low [Chl-a] values ( $<0.03 \text{ mg m}^{-3}$ )

Dataset	<i>RMSE</i> $\text{mg m}^{-3}$	<i>R</i> <sup>2</sup>	Slope	<i>MAE</i> $\text{mg m}^{-3}$	<i>MAPE</i>	Bias $\text{mg m}^{-3}$	Log- <i>MAE</i>	Log-Bias	<i>N</i>
Training	0.249	0.890	0.917	0.0987	22.90	0.0118	1.218	1.038	22624044
Test	0.247	0.891	0.933	0.101	23.14	0.0131	1.220	1.036	22647



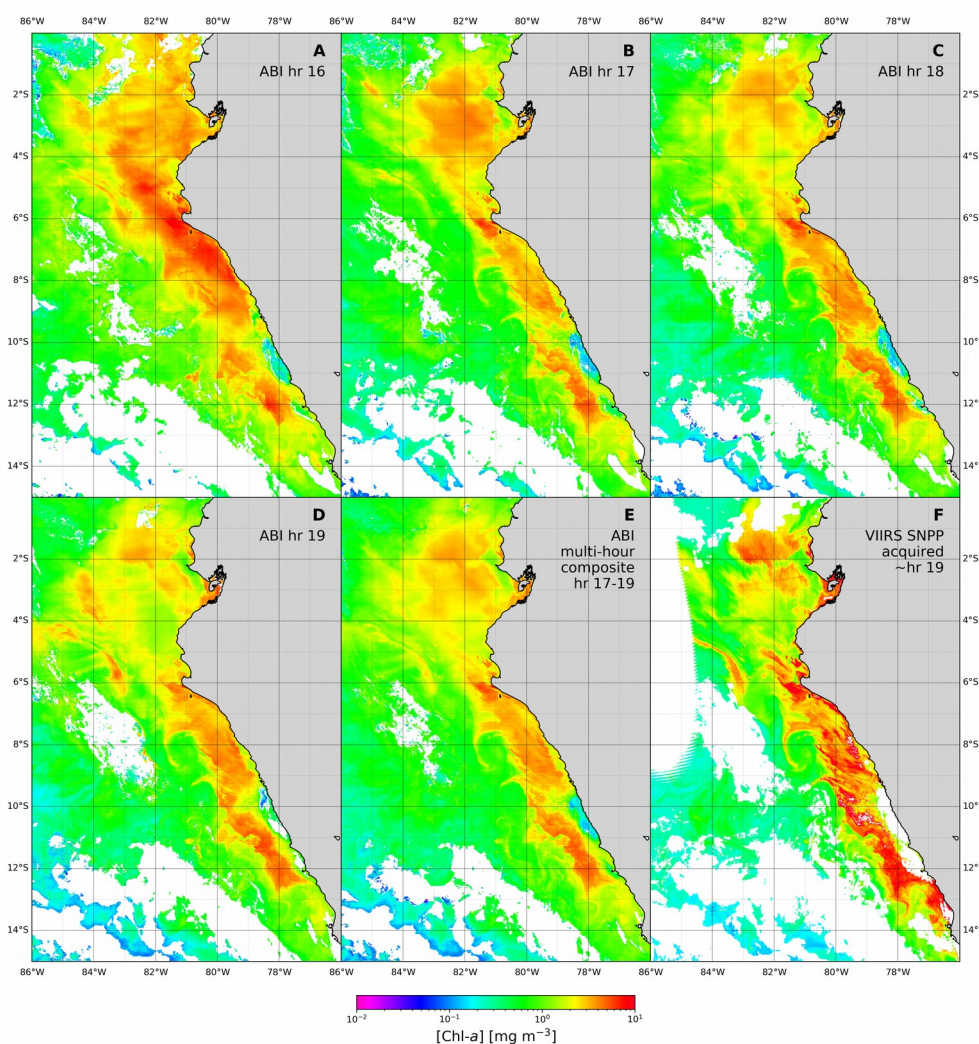


# ABI Hourly composite

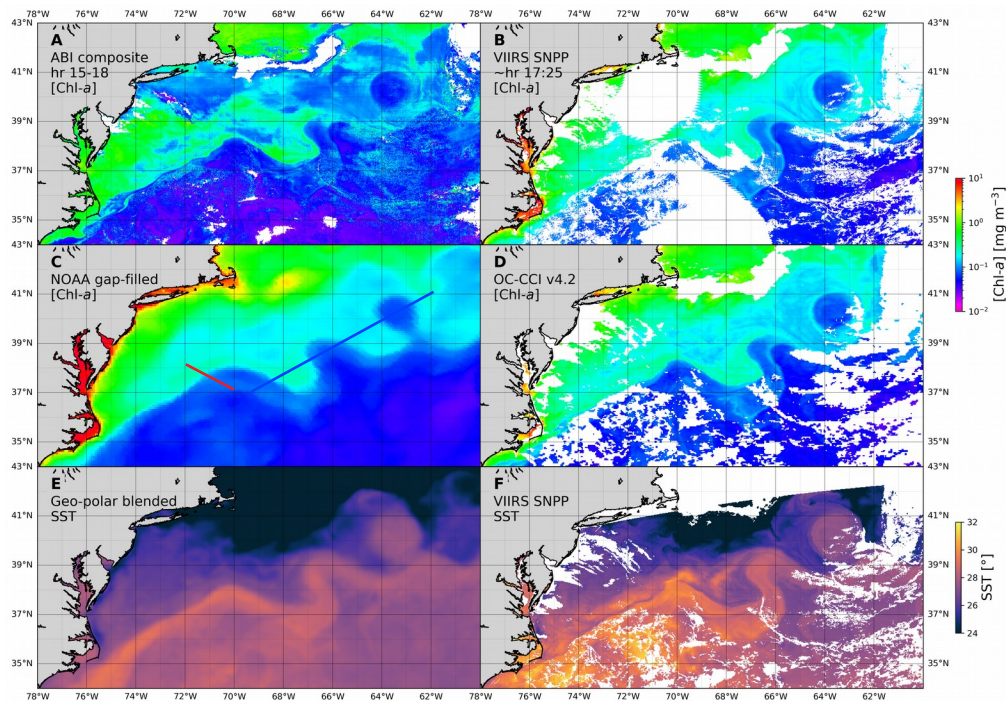
## Chilean coastal upwelling



- Hours around local noon agree better with VIIRS
- Magnitude is underestimated but spatial features are well preserved
- Improved data coverage than VIIRS

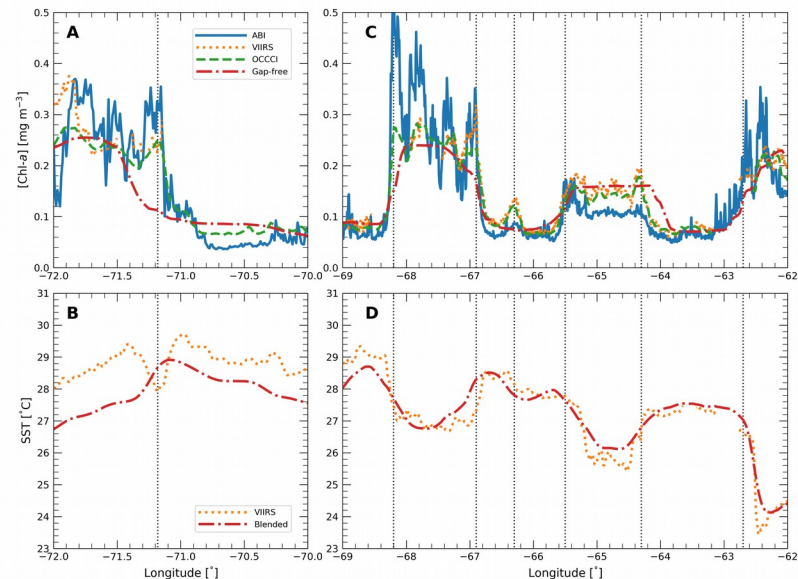


# Comparison with [Chl-a] and SST products Gulf Stream



Transect

Transect



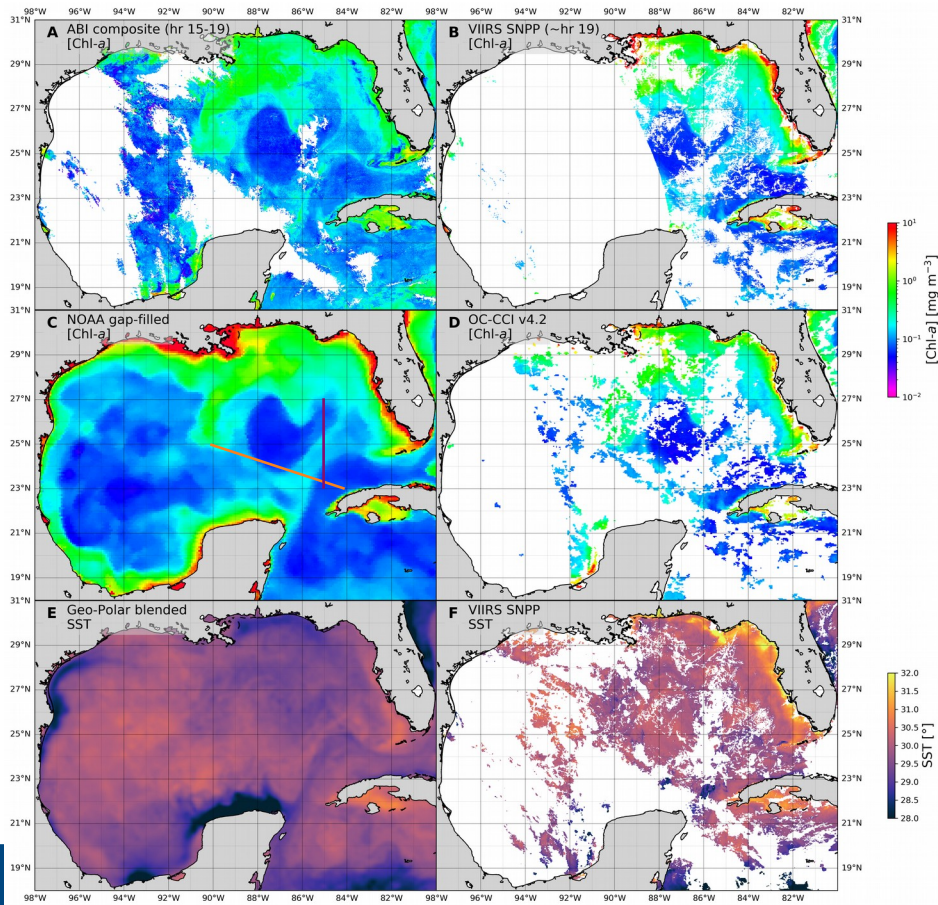
- Front detection: ABI agrees with VIIRS and OC-CCI
- Gap-free [Chl-a] and SST captures general but not detailed features



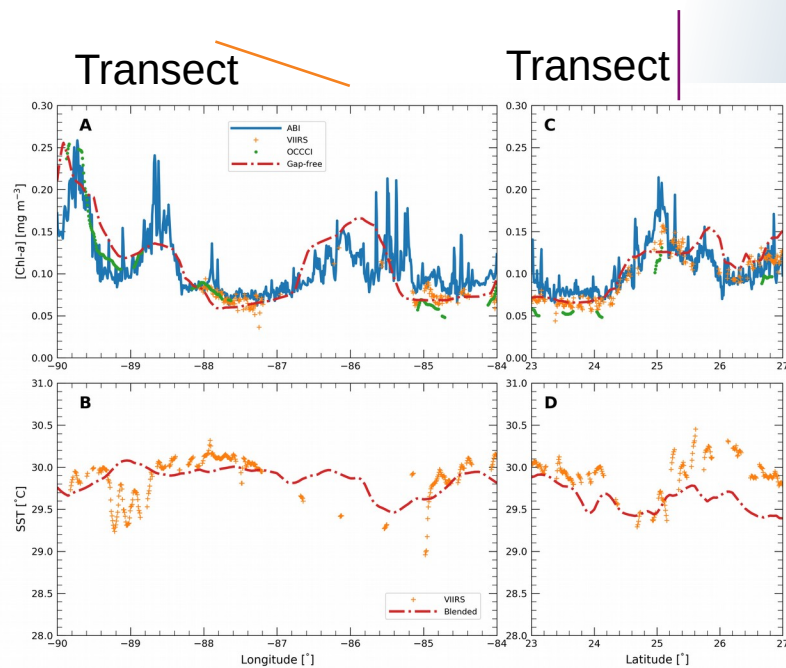


# Comparison with [Chl-a] and SST products

## Gulf of Mexico



- Small SST but large [Chl-a] gradients
- Extended state of Loop Current



# Summary



- We demonstrated the proof-of-concept to retrieve [Chl-a] for the open oceans using GOES-R ABI which was previously considered unfit for ocean color applications owing to the lack of a green band.
- The deep learning model is good at frontal feature detection although the input radiance data were not processed with any atmospheric correction. This suggests that deep learning can recognize subtle patterns barely perceptible to the human eye.
- Deep learning is a powerful tool to take into account a diverse set of input variables that are difficult for human to handle simultaneously. In this case, radiances, sun-sensor geometry, and julian day.
- Next steps: Add ancillary data being used for atmospheric correction. Detection of “bad” pixels.



# Acknowledgement

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